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W-net: A Dual-domain Deep Learning Model for Image Reconstruction

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Summary

Many images are acquired on a specific sensor (or encoded) domain, such as the frequency domain or the discrete cosine domain, prior to being reconstructed (or decoded) into an interpretable image. In this presentation, we present the W-net, a deep-learning-based dual-domain model, to reconstruct images. We illustrate its application to reconstruct (decode) sparsely sampled magnetic resonance (MR), low-dose computed tomography (CT) and JPEG compressed images.

Method Overview

Our dual-domain model (Figure 1) reconstructs images by leveraging local correlations as presented in the encoded and decoded domains. The method is composed of an encoded-domain network and a decoded-domain network connected through the appropriate domain transform. The architecture of the individual networks are U-nets [1] (the concatenation of two U-nets suggests the name of our model: W-net). At the end of each U-net, optional data consistency layers can be incorporated to include domain specific knowledge to the reconstruction process. For instance, data consistency in the MR sparse sampling image reconstruction problem is implemented by enforcing that the measured values at the sampled positions values in the frequency domain are preserved throughout the reconstruction process. For JPEG decompression, data consistency is implemented by enforcing that the discrete cosine transform coefficients are within the set of feasible coefficients, which is determined through the quantization matrix used in the compression process. For low-dose CT denoising, no data consistency was employed. The encoded domain for MR and CT reconstruction processes is the frequency-encoded domain, while for the JPEG-decompression problem the encoded domain is the discrete cosine transform (DCT) domain taken across 8×8 image patches. For further details on the methodology, we refer the reader to [2-4].

Results

We tested our W-net model on 1) 1,700 MR slices with a sampling rate of 20%, 2) 16,110 JPEG-compressed images with quality factors ranging between 10 and 19, and 3) 2,373 low-dose CT images. For the MR reconstruction and the JPEG-decompression problems, we used a mean squared error metric to train the W-net models. For the CT denoising, we used a modified perceptual loss function [4]. Our W-net model improved 1) MR reconstruction peak signal-to-noise ratio (pSNR) by nearly 6 dB compared to zero-filled reconstructed images, 2) JPEG restoration by 1 dB compared to standard JPEG-decompression and 3) CT by 4.8 dB compared to conventional low-dose CT baselines. Sample reconstructions for each problem are depicted in Figure 2.

Novelty of Our Model

The main novelty of our model is the dual-domain component that leverages local correlations across both the encoded and decoded domains. Also, unlike other reconstruction techniques, *cf.*, [5], we do not need to learn the domain transform, which has a quadratic complexity in terms of learnable parameters and poses hardware difficulties when working with images larger than 128 × 128 pixels. Domain-specific information is incorporated into our model through the data consistency layers, which improve reconstruction and help prevent overfitting of the model.

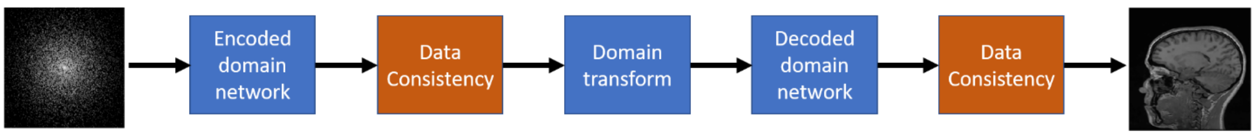

Figure 1. Flowchart of our dual-domain model. It consists of two networks, one in the encoded domain and the other in the decoded domain. These networks are connected through the appropriate domain transform (*e.g.*, Fourier Transform). We use U-nets as the base network. The term W-net comes from the fact that our model consists of the concatenation of two U-nets. These blocks are represented in blue in the diagram. Data consistency layers, depicted in brown in the diagram, are optional blocks that seek to enrich the learning process by incorporating problem specific prior knowledge.

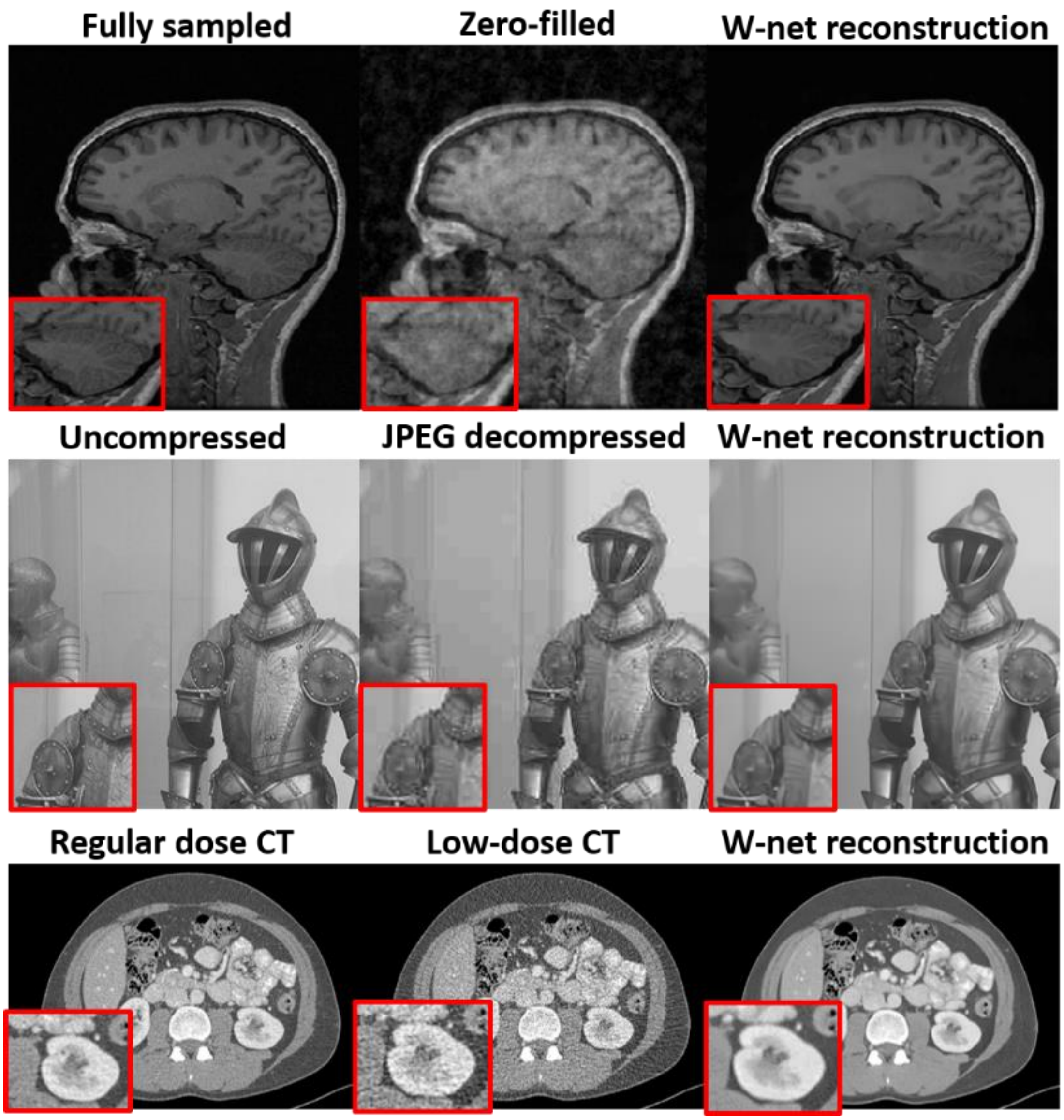

Figure 2. Sample reconstruction results of our W-net model for MR reconstruction (top row), JPEG-compressed image reconstruction (middle row) and CT denoising (bottom row). The red squares magnify a region of interest. Visual inspection of the images indicates the superiority of the W-net model reconstructions compared to their counterparts – zero-filled, standard JPEG decompression, and low-dose CT.

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